

A Deep learning method for real-time intraoperative US image segmentation in prostate brachytherapy

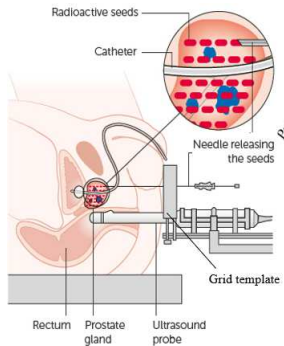
Kibrom B. Girum, Gilles Créhange, Raabid Hussain,
Alain Lalande

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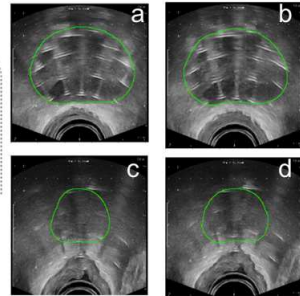
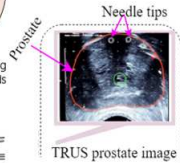
Prostate brachytherapy

A typical intra-operative procedure in permanent brachytherapy



A

A. Schematic representation



B

B. Prostate TRUS images

Prostate clinical target volume segmentation

Objective

- To develop a robust and automatic method for prostate gland segmentation in intra-operative TRUS images

Challenges

- Large variations of prostate size and shape
- Low-contrast at the edge of the prostate gland
- Inherent high artifacts of ultrasound imaging
- Strong artifact signals from the needle and the implanted seeds

Hypothesis

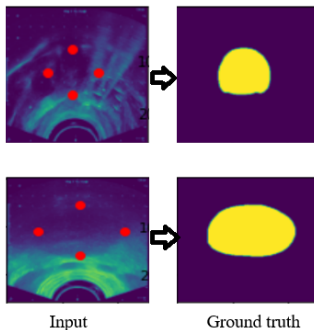
Learning-based shape reconstruction from automatically sampled prostate boundary coordinates along with the deep learning-based pixel classification (e.g., U-net) can automatically detect the low-contrast and noisy region of the prostate in TRUS images.

Dataset

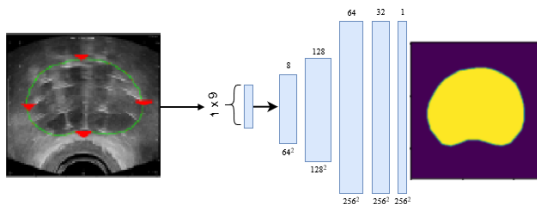
- Transrectal ultrasound (TRUS) images
 - 145 TRUS exams
 - Permanent prostate brachytherapy with ^{125}I
 - Plane resolution of 0.1038 x 0.1038
 - The series of transverse 2D TRUS images were acquired at 1 mm intervals

Pre-processing

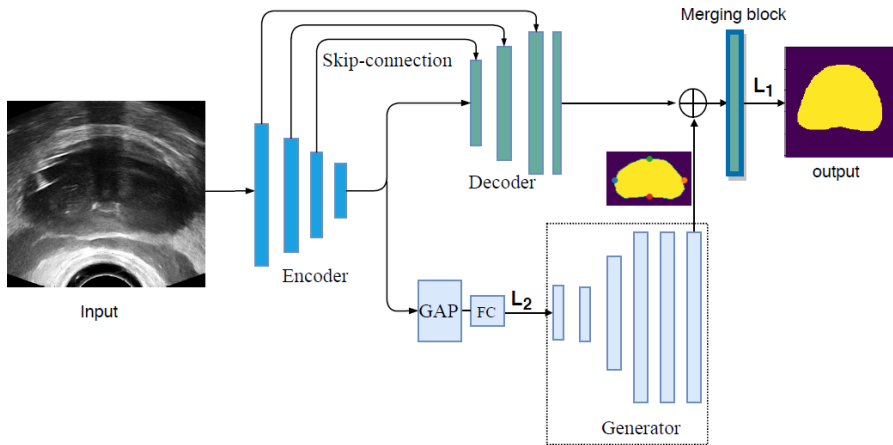
- Resized to $0.25 \times 0.25 \times 1 \text{ mm}^3$
- Center cropped to an image resolution of $256 \times 256 \times 64$
- Extracted four extreme coordinate points of the prostate from the ground truth for the training



Mask generator



- Binary cross-entropy loss function
- Regression for surface coordinates x and y
- Image based classification from z direction



Proposed end-to-end architecture

Loss function

$$L = \gamma L_1 + (1 - \gamma) L_2, \quad (1)$$

where L_1 is the segmentation cost function (i.e., $L_1 = L_{dice} + L_{bce}$) and L_2 is the classification and regression cost function.

$$L_2(I^u, I^v) = L_{cls}(p, s^u) + \lambda \times s^u (1 - Regression), \quad (2)$$

$$Regression = \left(\frac{1}{1 + \sum_{i \in \{x, y, s=1\}} smooth_{L1}(t_i^u - t_i^v)} \right), \quad (3)$$

Ablation study

Metric	U-net	U-net + Se	U-net + Se + Gn
DSC	0.79 ± 0.04	0.87 ± 0.02	0.88 ± 0.03
HD95	4.05 ± 0.63	2.38 ± 0.58	2.01 ± 0.54

U-net: Convolution + activation + Batch normalization

U-net + Se: U-net + squeeze-and-excitation network¹

U-net + Se + Gn: U-net + Se + generator

DSC: Dice Similarity Coefficient

HD95: 95% Hausdorff distance (in mm)

¹Hu J, et al. Squeeze-and-excitation networks. CVPR, 2018

Comparison of experimental results

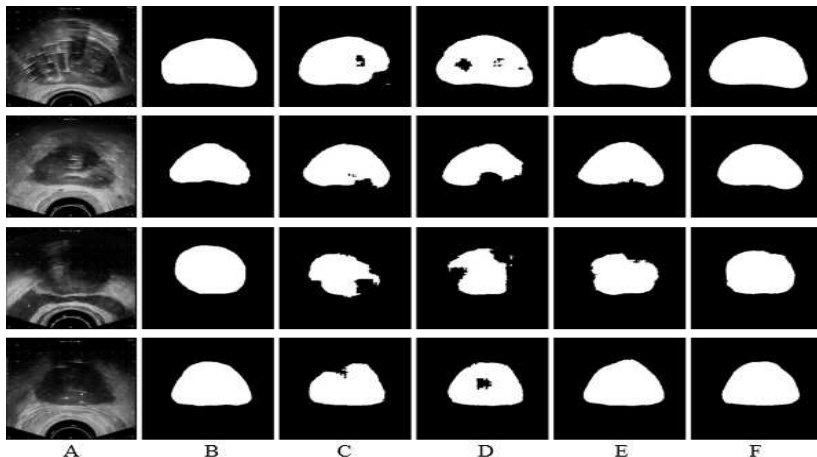
Metrics	U-net	Res-Unet	Res-Se-Unet	Proposed
DSC	0.79 ± 0.04	0.78 ± 0.04	0.86 ± 0.03	0.88 ± 0.02
HD95	4.05 ± 0.63	4.40 ± 0.74	3.17 ± 1.45	2.01 ± 0.54
HD	16.0 ± 7.60	15.2 ± 6.27	14.79 ± 5.98	8.37 ± 2.93
Sn	0.79 ± 0.07	0.80 ± 0.07	0.92 ± 0.03	0.88 ± 0.05
Sp	0.96 ± 0.01	0.96 ± 0.02	0.96 ± 0.02	0.98 ± 0.01
Acc	0.93 ± 0.02	0.93 ± 0.02	0.95 ± 0.95	0.96 ± 0.01
Asd	0.33 ± 0.18	0.41 ± 0.21	0.33 ± 0.11	0.10 ± 0.06

Sn: sensitivity

Sp: Specificity

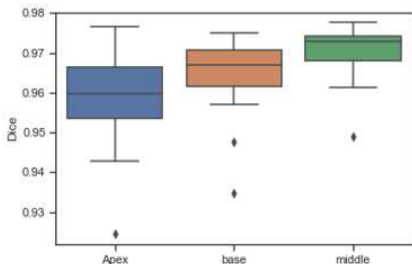
Asd: Average surface distance

Qualitative results

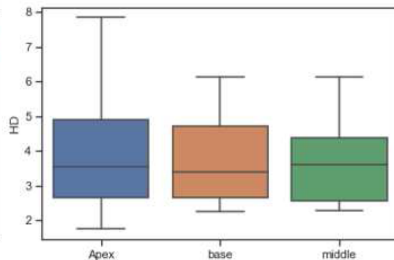


(A) Input image, (B) Ground truth labels, (C) U-net, (D) Res-Unet, (E) Res-Se-Unet and (F) proposed method

Mask generator results



(a)



(b)

- Average Dice similarity coefficient of 0.97
- Average Hausdorff distance error of 4.11 mm

Summary and remarks

Take home message

- Embedding prior organ knowledge via learning-based shape modeling and registration can improve image segmentation
- The prostate shape can be generated from a few sampled boundary coordinates
- Channel-wise feature calibration network enhances the performance of deep learning method

Future work

- Use the spatial-temporal information between adjacent slices
- Train the generator from MRI images

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